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(54) **Virtual vehicle sensors based on neural networks trained using data generated by simulation models**

Virtuelle Fahrzeugsensoren auf der Basis neuronaler Netze, die mittels durch Simulationsmodelle erzeugter Daten angelernt werden

Capteurs virtuels pour vehicules basés sur des réseaux neuronaux entrainés à partir de données générées par des modèles de simulation

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US-A- 5 583 964

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Description

[0001] The present invention relates to virtual vehicle sensors which use neural networks trained using a simulation model to monitor a vehicle parameter.

[0002] Modern engines utilise an electronic engine control module (ECM) to continuously monitor and control engine operation to optimize fuel economy, emissions control, and performance. The ECM uses various physical sensors to collect information reflecting current operating conditions. The information is used to generate output signals for various actuators which control operation of the engine. Using the actuators, the ECM controls the air-fuel ratio, fuel injection, ignition timing, and various other functions to control operation of the engine. Optimal control of the engine over a wide range of engine operating conditions (and ambient conditions) depends on the availability, accuracy, and reliability of data gathered by the engine sensors.

[0003] An ideal engine control system would be capable of directly measuring each engine operating parameter which affects any control variable. However, any realizable design is subject to considerations such as the cost, durability, repairability, and/or technological feasibility (including packaging considerations) of appropriate sensors. The deployment of more and more physical sensors results in per-unit cost penalties in development and manufacturing. Replacement and repair costs also rise due to the increased number of sensors and difficulty in diagnosing sensor malfunctions. As such, actual systems typically involve design compromises to accommodate technological difficulties and reduce the cost and complexity of the physical system employed to monitor and control the engine. It is therefore desirable to improve the availability, accuracy, and reliability of data used to effect engine control without significantly impacting the cost, complexity, or repairability of the vehicle.

[0004] US-A-5 539 638 describes a method of monitoring the operation of an internal combustion engine with a plurality of monitoring sensors. A predictive model processor is provided that uses model parameters stored in a memory to predict from the sensor inputs a predicted emissions output. The model is trained by means of a training database generated with inputs provided by the sensors and an actual emissions sensor output.

[0005] The present invention uses one or more neural networks within the ECM which act as virtual sensing devices to replace or enhance traditional physical engine sensors.

[0006] The present invention provides a method of manufacturing a sensor for use with a vehicle component having a controller in communication with a plurality of physical sensors each generating a signal indicative of first operating parameters, the sensor determining values for a second operating parameter based on values for the plurality of first operating parameters, the method comprising the steps of:

monitoring signals generated by the plurality of physical sensors to generate test data representative of values for the first operating parameters for a first set of operating conditions; and
embedding a trained neural network into the controller to determine values for the second operating parameter based on values for the plurality of first operating parameters;

characterised in that the method further comprises;

calibrating a simulator for simulating operation of the vehicle using the test data;
generating at least one map which characterizes performance of the vehicle component as a function of predetermined parameters, the map being based on output of the simulator for a second set of operating conditions; and
adjusting weights corresponding to nodes of the neural network based on the at least one map so as to train the neural network.

[0007] Numerous advantages are associated with the present invention. For example, the present invention allows sensing of operating parameters which are currently difficult or cost-prohibitive to measure directly. The present invention utilizes simulation models to generate more comprehensive data representing more operating conditions than would be economically feasible using traditional testing and mapping. The comprehensive data results in more accurate training of the neural networks thereby leading to a more accurate sensor. The sensor may be used to provide monitoring of fundamental physical quantities characterizing operation of the vehicle components which are otherwise unavailable using physical sensors. The present invention is applicable to a wide variety of control systems although particularly suited for control of vehicle engines.

[0008] The invention will now be described, by way of example, with reference to the accompanying drawings, in which:

Figure 1 is a block diagram illustrating an engine control application utilizing one embodiment of the present invention;
Figure 2 is a block diagram illustrating a virtual sensor based on a neural network structure according to the present invention; and
Figure 3 is a flowchart illustrating a method for developing and manufacturing a virtual sensor according to the present invention.

[0009] Referring now to Figure 1, a block diagram is shown illustrating one potential application for a virtual sensor according to the present invention. A control sys-

tem 10 includes a vehicle component such as engine 12 in communication with a controller 14. System 10 includes a plurality of physical sensors, indicated generally by reference numeral 16. Any number of physical sensors 16 may be used depending upon the particular application and the particular vehicle component being controlled. Physical sensors 16 may include a mass air flow (MAF) sensor 18, a throttle position sensor (TPS) 20, an engine speed sensor (RPM) 22, and/or a coolant temperature (TMP) sensor 24.

[0010] In many gasoline-powered automotive applications, engine 12 is coupled to a catalytic converter 26 via an exhaust pipe 28. Catalytic converter 26 is typically coupled to a muffler (not specifically illustrated) via exhaust pipe 30. In these applications, additional physical sensors 16 may include an upstream exhaust gas oxygen (EGO) sensor 32, a downstream EGO sensor 34, and a catalytic converter temperature sensor 36. Various other vehicle sensors may also be included, such as vehicle speed sensor (VSS) 38 and manifold absolute pressure (MAP) sensor 39.

[0011] In operation, controller 14 monitors signals generated by physical sensors 16 to determine values for the corresponding operating parameters of engine 12. Signals generated by physical sensors 16 are communicated to one or more input ports 40. Appropriate signal conditioning, buffering, circuit protection, and signal conversion is typically provided by circuitry within controller 14. For example, a temperature signal generated by coolant temperature sensor 24 may be filtered, buffered, and converted to a digital signal by the circuitry within controller 14 prior to passing through input ports 40.

[0012] Controller 14 of Figure 1 preferably includes a microprocessor unit (MPU) 42 in communication with various computer-readable storage media, indicated generally by reference numeral 44. Computer-readable storage media 44 may include various types of volatile and non-volatile memory such as keep-alive memory (KAM) 46, read only memory (ROM) 48, and random access memory (RAM) 50. Computer-readable storage media 44 communicate with microprocessor 42 via address and data bus 52. Microprocessor 42 processes values corresponding to various operating parameters as indicated by the signals received through input ports 40 in accordance with data and instructions stored in computer-readable media 44.

[0013] Microprocessor 42 generates control and command signals which are communicated via output ports 54 to various actuators, indicated generally by reference numeral 56. Actuators may include a fuel controller 58 which provides appropriate signals for one or more fuel injectors (not specifically illustrated). Other actuators may include a spark controller 60 and an exhaust gas recirculation (EGR) valve 62. EGR valve 62 is used to control the amount of exhaust gases routed from exhaust 28 to intake 64 via plumbing 66.

[0014] As also illustrated in Figure 1, controller 14 includes a neural network-based virtual sensor 68 according to the present invention. The virtual sensor is preferably embedded within controller 14 and may exist across or within one or more computer-readable storage media 44. For example, various instructions may be stored in one type or one physical storage media while working data is stored in another physical device which may or may not be of the same type of storage media.

[0015] Virtual sensor 68 may be used to determine a value for an engine operating parameter which is difficult or costly to measure directly. Values for various physical-based parameters are input to virtual sensor 68, such as those values which represent the physical signals generated by physical sensors 16. Various other signals may provide input to virtual sensor 68 to dynamically determine values for various engine operating parameters. Such signals may be indicative of air/fuel ratio, cam timing, air charge temperature, oil temperature, and the like. Virtual sensor 68 forms a linear combination of non-linear functions of physically-based parameters. Virtual sensor 68 then determines values for various other engine operating parameters which are difficult to measure. Such parameters may include residual mass fraction, emissions, knock index, peak pressure rise rate, exhaust gas temperature, and exhaust gas oxygen content. The output from one or more virtual sensors enables controller 14 to better account for the internal processes of engine 12. This information may be used to improve control of engine 12 by adjusting various functions such as spark timing, EGR level, fuel injection timing, cam timing, or fuel pulsewidth to minimize fuel consumption, emissions, knock tendency, engine instability, and noise, vibration, and harshness (NVH) effects. As such, the present invention improves engine control by providing information representing dynamic engine state conditions based on various non-linear relationships among physical-based signals. The non-linear relationships are captured automatically by the neural network during training, as described in greater detail herein.

[0016] Referring now to Figure 2, a block diagram illustrating a neural network structure for a virtual sensor according to the present invention is shown. Virtual sensor 68 includes various inputs 80 generated by physical sensors and/or other virtual sensors. An input layer 82 includes nodes 84 associated with each of the inputs 80. The neural network-based sensor 68 also includes one or more hidden layers 86 and an output layer 88. Nodes 84 of input layer 82 communicate with one or more nodes 90 of hidden layers 86 via connections 92. During training of the network, the various connections along with associated weights are determined. Block 94 represents a polynomial function of its inputs to generate a sensor output 96. The degree of the polynomial employed in block 94 is constrained to be one less than the number of nodes in output layer 88. For most virtual sensors, a feed-forward neural network will provide satisfactory performance. It should be recognized, howev-

er, that the number and structure of nodes for each layer will vary depending upon the particular parameter being determined.

[0017] The particular structure illustrated in Figure 2 depicts a neural network for a set of engine performance variables using knowledge that most of the variables are low-order polynomial functions of the spark input when all the other parameters are fixed. Instead of predicting the output directly, the neural network of Figure 2 predicts the polynomial coefficients represented by block 94 as functions of the other engine operating parameters. It should be noted that this type of neural-regression model is not restricted to the use of polynomials as any functional module may be employed which allows determination of the partial derivatives of the module's output with respect to the neural network's weights to be computed.

[0018] Indeed, the choice of non-polynomial functions is often preferred because of the tendency of interpolating polynomials to exhibit large errors when used to extrapolate outside the bounds of the underlying data.

[0019] Once a particular network structure or model is determined, the training of the network or the adjustment of the weights associated with each of the connections 92 between nodes or neurons can be carried out using established algorithms, such as the Levenburg-Marquardt algorithm or the Node Decoupled Extended Kalman filter algorithm developed by Puskorius and Feldkamp. For some engine control applications, the latter algorithm exhibits superior convergence properties resulting in faster training of the network while also yielding networks possessing better generalization capabilities compared to simple back propagation algorithms. It is desirable to utilize an architecture which is capable of representing a particular parameter map to a desired degree of accuracy while lending itself to automatic training procedures as explained and illustrated with reference to Figure 3.

[0020] Referring now to Figure 3, a flowchart illustrating a method for manufacturing or developing neural network-based virtual sensors is shown. Block 100 represents the generation of test data during operation of a vehicle component, such as an engine. The test data provides representative values for a plurality of operating parameters for a particular set of operating conditions. To capture the relationship among the various inputs over all the operating conditions, it is desirable to generate a large set of data which reflects the typically non-linear relationship among basic engine operating parameters and the desired sensor output. Typically, this objective cannot be accomplished using conventional dynamometer testing alone because some engine parameters are not easily measured, and such a comprehensive map would be cost prohibitive. As such, the present invention requires only enough test data to calibrate a physically-based simulation model as represented by block 102.

[0021] Preferably, test data generated in block 100 is used to calibrate the simulation model represented by block 102 at one or several representative "anchor" points. The simulation program can then be used to interpolate or extrapolate a more complete set of data as represented by block 104. This comprehensive map characterizes performance of the vehicle component as a function of predetermined design and control parameters. This information is then used to program or train the neural network-based virtual sensor as represented by block 106. The sensor is then embedded in the controller in the form of data and instructions as represented by block 108.

[0022] The model-based mapping using established first principle parametric simulation models requires only about 1% of the experimental test data compared to the data required for a full empirical map. As such, the present invention has the potential for a two-thirds savings in cost while reducing the time required to generate a complete map from about a month to the order of a week.

[0023] As described above, the present invention may be utilized to provide a virtual sensor for any of a number of operating parameters for various vehicle components to realize a "virtual" closed-loop control system. As an example, the present invention may be utilized to provide a virtual sensor for engine control systems which dynamically determine the residual mass fraction using various physically-based sensor inputs.

[0024] The residual mass fraction (RMF), as used herein, refers to that fraction of the cylinder contents trapped in the current cycle which has been burned in some previous cycle. This may also be referred to as the burned gas fraction. RMF has both external and internal sources in conventional internal combustion engine operation. Exhaust gas recycling or recirculation (EGR) is the primary external source. EGR is introduced by routing some of the exhaust gases from the exhaust manifold back to the intake manifold via external plumbing. The amount of EGR introduced into the intake is regulated by an EGR valve at the point where the exhaust gases enter the intake manifold. The internal source (sometimes referred to as internal EGR) arises due to the inability of the gas exchange process in conventional engine designs to completely replace the burned gases with fresh air/fuel mixture. The amount of residual is influenced by the setting of the EGR valve, the throttle position, and the valve overlap, i.e. the period of time where both the intake and exhaust valves are open. Excessive dilution by residual from any source can degrade combustion quality. However, limited levels of residual under throttled operation have beneficial effects on emissions and fuel economy.

[0025] As RMF increases, it displaces fresh charge. In order to trap the fuel and air required to maintain the required level of engine torque output, the throttle must be opened up so that more total gases become trapped in the combustion chamber. The heat liberated by the combustion is distributed over a larger mass, thus low-

ering peak temperatures during combustion. Production of oxides of nitrogen (NO_x), being very sensitive to combustion temperature, is thereby reduced significantly. Opening up the throttle valve also increases the intake pressure which reduces throttling losses and improves fuel economy.

[0026] It is common practice to use EGR to control the level of RMF to maximize fuel economy and minimize NO_x emissions at each speed and torque throughout the operating range of the engine. The appropriate amount of EGR is generally determined experimentally by testing the engine at each condition on a dynamometer prior to installation in the vehicle. The engine controller is then programmed to supply the correct level of EGR as a function of engine speed and torque.

[0027] With the advent of variable valve timing mechanisms as practical in-vehicle devices, the level of internal EGR can be controlled by changing the opening and closing times of the intake and exhaust valves. This method of controlling RMF can either supplant or complement the external EGR system. A control strategy analogous to the EGR methodology could be devised for variable valve timing. One could find an optimal valve timing at each operating condition and program the resulting set into the engine controller.

[0028] In either case, RMF is the fundamental engine parameter which is being controlled. The present invention may be utilized to develop a more robust control strategy since RMF may be dynamically determined and therefore controlled. Once the value for a particular parameter (RMF in this case) can be directly determined, traditional control techniques may be applied, i.e. comparing the measured value to the optimal, and adjusting either EGR or valve timing to correct any deviation.

[0029] The cycle simulation program used according to the present invention calculates the thermodynamic state of the engine as a function of time, or crank angle, during the combustion cycle. The simulation tracks pressures, temperatures, and composition of the gases in the cylinder, intake system, and exhaust system by solving a set of differential equations. The composition of the cylinder is governed by the conservation equations for total mass and fresh charge fraction:

$$m\dot{c} = \dot{m}_i\hat{c}_i - \dot{m}_e\hat{c}_e$$

$$\dot{m} = \dot{m}_i - \dot{m}_e$$

$$r = l - c$$

where:

- m represents the total mass in the cylinder,
- c represents the mass fraction of fresh charge in the cylinder,
- r represents the RMF in the cylinder,
- $\dot{m}_i$ represents the mass flow rate into the cylinder through the intake valve(s),
- $\dot{m}_e$ represents the mass flow rate out of the cylinder through the exhaust valve(s),
- $\hat{c}_i$ represents the charge fraction associated with $\dot{m}_i$ (c if $\dot{m}_i < 0$, c_i if $\dot{m}_i > 0$),
- $\hat{c}_e$ represents the charge fraction associated with $\dot{m}_e$ (c if $\dot{m}_e > 0$, c_e if $\dot{m}_e < 0$,
- c_i represents charge fraction of gas residing in the intake port, and
- c_e represents charge fraction of gas residing in the exhaust port.

[0030] The engine can then be tested at all the relevant speed/torque combinations representative of its operating range. At each point, dilution RMF can be varied by changing EGR and/or valve timing as previously described. The cycle simulation program can be used to calculate the value of RMF as these parameters are varied to generate a comprehensive map. When the optimal level of dilution is ascertained, the associated RMF is established as the target value for that speed and torque.

[0031] Meanwhile, the cycle simulation program can be used to calculate RMF as a function of all engine operating parameters (speed, torque, EGR, valve timing, spark advance, inlet temperature, etc.) These results can then be used to construct the virtual RMF sensor. If the virtual sensor is implemented through a neural net, these data comprise the training set by which the net learns the functional dependence of RMF on various other physical-based operating parameters. Of course, a virtual sensor according to the present invention may also use the outputs from various other virtual sensors as inputs.

[0032] During operation in the vehicle, the controller interrogates the virtual sensor to determine the RMF associated with the current values for the operating parameters. This RMF value is compared to the previously determined optimal value for the current operating conditions as described above. If necessary, the controller can signal the actuator(s) controlling the appropriate parameter(s) e.g, valve timing to move RMF toward the optimal value.

Claims

1. A method of manufacturing a sensor (68) for use with a vehicle component (12) having a controller (14) in communication with a plurality of physical sensors (16) each generating a signal indicative of first operating parameters, the sensor (68) determining values for a second operating parameter based on values for the plurality of first operating parameters, the method comprising the steps of:

monitoring (100) signals generated by the plurality of physical sensors (16) to generate test data representative of values for the first operating parameters for a first set of operating conditions; and

embedding (108) a trained neural network into the controller (14) to determine values for the second operating parameter based on values for the plurality of first operating parameters;

characterised in that the method further comprises;

calibrating (102) a simulator for simulating operation of the vehicle using the test data;

generating (104) at least one map which characterizes performance of the vehicle component as a function of predetermined parameters, the map being based on output of the simulator for a second set of operating conditions; and

adjusting (106) weights corresponding to nodes of the neural network based on the at least one map so as to train the neural network.

2. A method as claimed in claim 1, wherein the vehicle component comprises an engine (12) and wherein the step (100) of monitoring signals generated by the plurality of physical sensors to generate test data representative of values for the first operating parameters for a first set of operating conditions comprises operating the engine (12) on a dynamometer.

3. A method as claimed in claim 1 or 2, wherein the step (108) of embedding a trained neural network into the controller comprises storing a representation of the trained neural network in computer readable media (44), the representation including a plurality of instructions executable by a microprocessor (42) and data representing the weights corresponding to the nodes of the neural network.

4. A method as claimed in claim 1, 2 or 3, wherein the step (106) of adjusting weights corresponding to nodes of the neural network comprises adjusting weights corresponding to monotonically increasing piecewise differentiable function nodes of the neural network.

5. A method as claimed in claim 1, 2, 3 or 4, further comprising the steps of;

processing the values for the first operating parameters using the trained neural network to determine a value for the second operating parameter; and

controlling the vehicle component based on the value of the second operating parameter.

6. A method as claimed in claim 5, wherein the step of processing the values for the first operating parameters using the trained neural network to determine a value for the second operating parameter comprises determining polynomial coefficients for the second operating parameter, the coefficients being functions of the first plurality of operating parameters.

7. A method as claimed in claim 5 or 6, wherein the step of processing the values for the first operating parameters using the trained neural network to determine a value for the second operating parameter is employed in relation to a second operating parameter lacking a physical sensor for directly providing values indicative of current operating conditions.

Patentansprüche

1. Ein Verfahren zur Herstellung eines Sensors (68) für die Verwendung mit einem Fahrzeugbauteil (12), das einen Regler (14) besitzt der mit einer Mehrzahl physikalischer Sensoren (16) in Verbindung steht, von denen jeder ein für erste Betriebsparameter kennzeichnendes Signal erzeugt; wobei der Sensor (68) auf Grundlage von Werten für eine Mehrzahl von ersten Betriebsparametern Werte für einen zweiten Betriebsparameter bestimmt, und wobei das Verfahren die Schritte umfaßt:

Überwachen (100) von - durch eine Mehrzahl von physikalischen Sensoren (16) erzeugten - Signalen; um Testdaten zu erzeugen, die für einen ersten Satz von Betriebsbedingungen für die ersten Betriebsparameter bezeichnend sind; und

Einbetten (108) eines trainierten neuralen Netzwerks in den Regler (14), um auf Grundlage einer Mehrzahl erster Betriebsparameter Werte für den zweiten Parameter zu bestimmen;

dadurch gekennzeichnet daß das Verfahren weiterhin umfaßt:

Kalibrierung (102) eines Simulators zur Simulation des Fahrzeugbetriebes unter Verwendung der Testdaten;

Erzeugen (104) mindestens einer Karte, welche die Leistung des Fahrzeugbauteils als Funktion vorherbestimmter Parameter charakterisiert, wobei die Karte auf der Simulatorausgabe für einen zweiten Satz von Betriebsbedingungen basiert; und

Justieren (106) von - Knoten des neuralen Netzwerkes entsprechenden- Gewichtungen

auf Grundlage dieser mindestens einen Karte, um so das neurale Netzwerk zu trainieren.

2. Ein Verfahren nach Anspruch 1, in dem das Fahrzeugbauteil einen Motor (12) umfaßt, und in dem der Schritt (100), in dem durch eine Mehrzahl physikalischer Sensoren erzeugte Signale überwacht werden, den Betrieb des Motors (12) auf einem Dynamometer umfaßt; um Testdaten zu erzeugen, die für die ersten Betriebsparameter für einen ersten Satz von Betriebsparametern repräsentativ sind.

3. Ein Verfahren nach Anspruch 1 oder 2, in dem der Schritt (108) zum Einbetten des trainierten, neuralen Netzwerks in den Regler die Speicherung einer Wiedergabe des trainierten neuralen Netzwerks in einem computerlesbaren Medium (44) umfaßt, und wobei die Wiedergabe eine Mehrzahl von Mikroprozessor (42) ausführbare Anweisungen und Daten einschließt, welche die - den Knoten des neuralen Netzwerks entsprechenden - Gewichtungsdaten darstellten.

4. Ein Verfahren nach Anspruch 1, 2 oder 3, in dem der Schritt (106) zur Justierung der - Knoten des neuralen Netzwerks entsprechenden - Gewichtungen die Justierung von Gewichtungen umfaßt, die monoton ansteigenden, stückweise ableitbaren Funktionsknoten des neuralen Netzwerks entsprechen.

5. Ein Verfahren nach Anspruch 1, 2, 3 oder 4, das weiterhin die Schritte umfaßt:

   Verarbeiten der Werte für die ersten Betriebsparameter unter Verwendung des trainierten neuralen Netzwerks, um einen Wert für den zweiten Betriebsparameter zu bestimmen; und
   Regeln des Fahrzeugbauteils auf Grundlage des Werts des zweiten Betriebsparameters.

6. Ein Verfahren nach Anspruch 5, in dem der Schritt zur Verarbeitung der Werte für die ersten Betriebsparameter - um unter Verwendung des trainierten, neuralen Netzwerks einen Wert für den zweiten Betriebsparameter zu bestimmen - die Bestimmung polynomischer Koeffizienten für den zweiten Betriebsparameter umfaßt; wobei die Koeffizienten Funktionen der ersten Mehrzahl von Betriebsbedingungen sind.

7. Ein Verfahren nach Anspruch 5 oder 6, in dem der Schritt zur Verarbeitung der Werte für die ersten Betriebsparameter unter Verwendung des trainierten neuralen Netzwerks - um einen Wert für den zweiten Betriebsparameter zu bestimmen - im Verhältnis zu einem zweiten Betriebsparameter angewendet wird; dem ein physikalischer Sensor für die direkte Bereitstellung von Werten fehlt, die für die gegenwärtigen Betriebsbedingungen bezeichnend sind.

Revendications

1. Procédé de fabrication d'un capteur (68) destiné à être utilisé avec un composant de véhicule (12) comportant un contrôleur (14) en communication avec une pluralité de capteurs physiques (16), chacun générant un signal indicatif de premiers paramètres de fonctionnement, le capteur (68) déterminant des valeurs pour un second paramètre de fonctionnement sur la base des valeurs pour la pluralité de premiers paramètres de fonctionnement, le procédé comprenant les étapes consistant à :

   surveiller (100) des signaux générés par la pluralité de capteurs physiques (16) afin de générer des données de test représentatives des valeurs pour les premiers paramètres de fonctionnement pour un premier ensemble de conditions de fonctionnement, et
   incorporer (108) un réseau neuronal ayant subi un apprentissage dans le contrôleur (14) afin de déterminer des valeurs pour le second paramètre de fonctionnement sur la base des valeurs pour la pluralité de premiers paramètres de fonctionnement,

   caractérisé en ce que le procédé comprend en outre,

   un étalonnage (102) d'un simulateur afin de simuler le fonctionnement du véhicule en utilisant les données de test,
   la génération (104) d'au moins une mappeou carte qui caractérise les performances du composant du véhicule en fonction des paramètres prédéterminés, la mappe étant fondée sur une sortie du simulateur pour un second ensemble de conditions de fonctionnement, et
   l'ajustement (106) des pondérations correspondant à des noeuds du réseau neuronal sur la base de la au moins une mappe de façon à faire subir un apprentissage au réseau neuronal.

2. Procédé selon la revendication 1, dans lequel le composant du véhicule comprend un moteur (12) et dans lequel l'étape (100) consistant à surveiller des signaux générés par la pluralité de capteurs physiques afin de générer des données de test représentatives des valeurs pour les premiers paramètres de fonctionnement pour un premier ensemble de conditions de fonctionnement comprend la mise en oeuvre du moteur (12) sur un dynamomè-

tre.

3. Procédé selon la revendication 1 ou 2, dans lequel l'étape (108) consistant à incorporer un réseau neuronal ayant subi un apprentissage dans le contrôleur comprend la mémorisation d'une représentation du réseau neuronal ayant subi un apprentissage dans un support lisible par un ordinateur (44), la représentation comprenant une pluralité d'instructions exécutables par un microprocesseur (42) et des données représentant les pondérations correspondant aux noeuds du réseau neuronal.

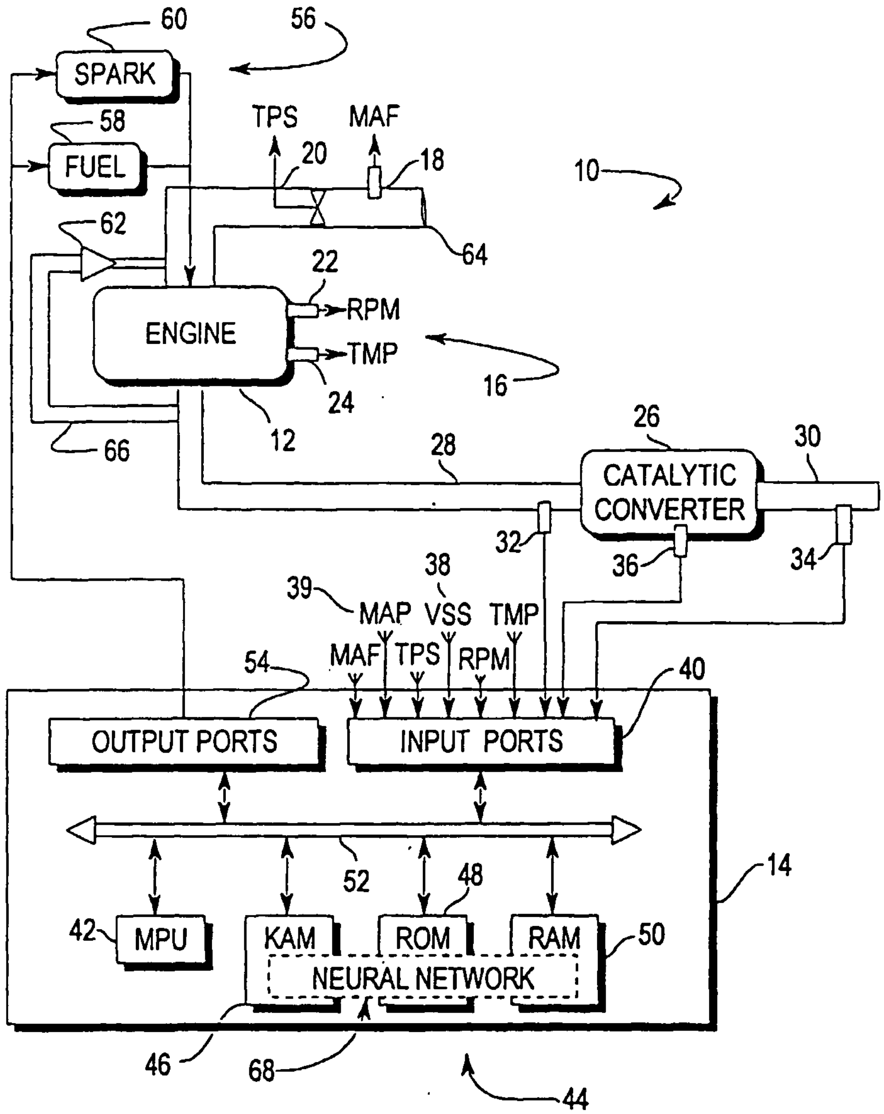
4. Procédé selon la revendication 1, 2 ou 3, dans lequel l'étape (106) consistant à ajuster des pondérations correspondant aux noeuds du réseau neuronal comprend l'ajustement des pondérations en correspondance avec des noeuds de fonctions différenciables augmentant individuellement de façon monotone du réseau neuronal.

5. Procédé selon la revendication 1, 2, 3 ou 4, comprenant en outre les étapes consistant à,

   traiter les valeurs pour les premiers paramètres de fonctionnement en utilisant le réseau neuronal ayant subi un apprentissage pour déterminer une valeur pour le second paramètre de fonctionnement, et
   commander le composant du véhicule sur la base de la valeur du second paramètre de fonctionnement.

6. Procédé selon la revendication 5, dans lequel l'étape consistant à traiter les valeurs pour les premiers paramètres de fonctionnement en utilisant le réseau neuronal ayant subi un apprentissage pour déterminer une valeur pour le second paramètre de fonctionnement comprenant la détermination des coefficients de polynôme pour le second paramètre de fonctionnement, les coefficients étant des fonctions de la première pluralité de paramètres de fonctionnement.

7. Procédé selon la revendication 5 ou 6, dans lequel l'étape de traitement des valeurs pour les premiers paramètres de fonctionnement en utilisant le réseau neuronal ayant subi un apprentissage pour déterminer une valeur pour le second paramètre de fonctionnement, est utilisée en relation avec un second paramètre de fonctionnement dépourvu de capteur physique afin de fournir directement des valeurs indicatives des conditions de fonctionnement en cours.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CATALYTIC
CONVERTER
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36
34
38
39
MAP
VSS
TMP
MAF
TPS
RPM
54
40
OUTPUT PORTS
INPUT PORTS
14
52
48
42
MPU
KAM
ROM
RAM
50
NEURAL NETWORK
46
68
44

Fig. 1

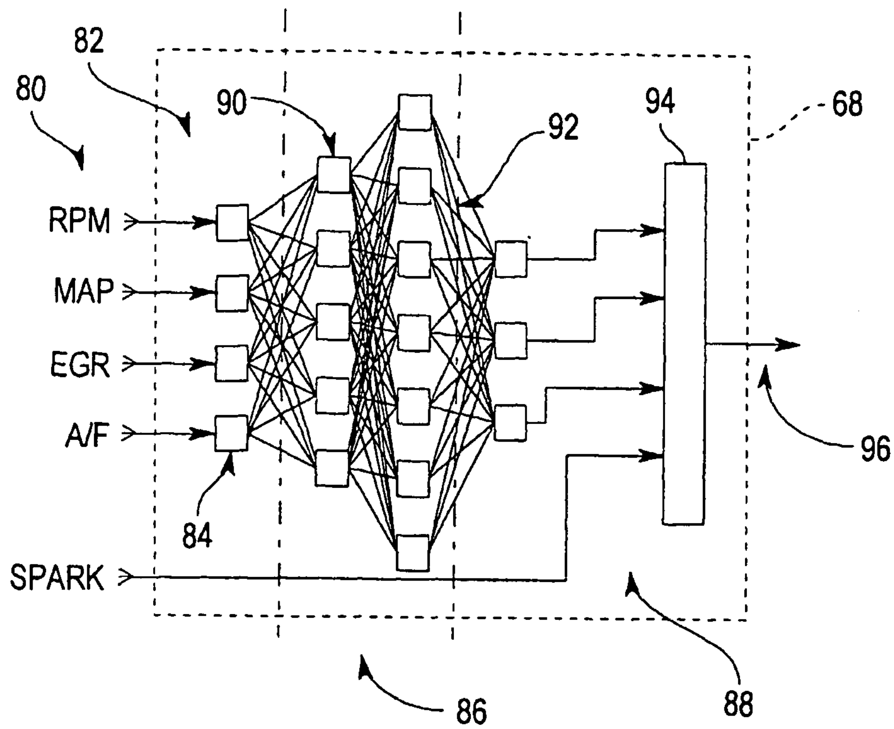

Fig. 2

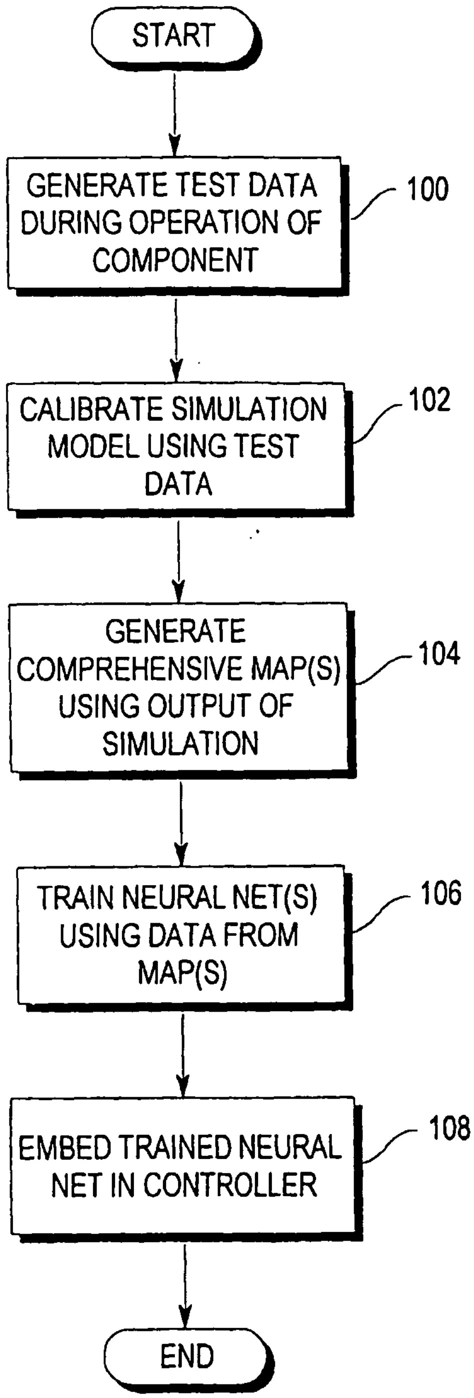
START
GENERATE TEST DATA DURING OPERATION OF COMPONENT
100
CALIBRATE SIMULATION MODEL USING TEST DATA
102
GENERATE COMPREHENSIVE MAP(S) USING OUTPUT OF SIMULATION
104
TRAIN NEURAL NET(S) USING DATA FROM MAP(S)
106
EMBED TRAINED NEURAL NET IN CONTROLLER
108
END

Fig. 3